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PRICE FORMATION UNDER SMALL NUMBERS COMPETITION: EVIDENCE FROM LAND AUCTIONS IN SINGAPORE

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Price Formation under Small Numbers Competition: Evidence from Land Auctions in Singapore

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Abstract

This paper examines the price formation process under small numbers competition using data from Singapore land auctions. The theory predicts that bid prices are less than the zero-profit asset value in these first-price sealed-bid auctions. The model also shows that expected sales price increases with the number of bidders both because each bidder has an incentive to offer a higher price and because of a greater likelihood that a high-value bidder is present. The empirical estimates are consistent with auction theory and show that the standard land attributes are reflected in auction prices as expected.

Keywords: Land auctions, price formation, small numbers competition

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1 Introduction

This paper examines the price formation process under small numbers competition. The neoclassical competitive bid price model envisions an implicit auction in which the highest bidding land use obtains the land and competition drives profits to zero. The model provides the foundation for modern land use theory and underlies most applied property markets analysis. The framework is easy to apply and capable of predicting how a variety of factors, including risk, affect the market price of land. The question of price formation, however, is subsumed within the competitive zero profit condition and therefore, by construction, the standard bid price model cannot evaluate the consequences of situations in which finite numbers of agents interact.

The literature has taken several alternative paths to study price formation in real estate markets. One approach focuses on the search and matching aspect of many property markets (particularly the housing market), an extensive line of literature that is growing rapidly. A second approach focuses on the negotiation process often observed in face-to-face real estate market transactions, typically relying on Nash bargaining or similar equilibrium constructs to model price formation. The empirical evidence in this line of literature is much less extensive, depending as it does upon data that is not widely available. These two approaches are similar in that they diverge from the standard competitive bid price equilibrium assumption, but differ in the market dimension upon which they focus: the role of search versus bargaining power in determining selling price. The third approach studies the performance of structured markets, like formal auctions, in which price formation is determined by well-defined rules governing bidding and acceptance by finite numbers of buyers and sellers.

This paper takes the third approach to studying price formation under small numbers competition. It begins with the recognition that the neoclassical bid price model depicts prices "as if" determined by auctions (although the structure of the implicit auction is not spelled out in any but the vaguest terms). It follows the logical connection of the implicit bid price-auction market nexus, beginning with a formal model of an auction process that yields the bid price formulation as a limiting case, then using the model to study the properties of the expected auction outcome as the finite number of participants varies.

Even though there are not many empirical studies of real estate auctions, the few that have been published are beginning to build a picture of regularities and anomalies. For example, there is a growing consensus that real estate sold in auctions appears to sell at a discount relative to full exposure to a market comprising searching buyers (Ashenfelter and Genesove, 1992; Mayer, 1998; Allen and Swisher, 2000; Ching and Fu, 2003). Other aspects of open-bid auctions, however, are not so clear-cut. For example, while Lusht (1994) and Mayer (1998) find that auction prices tend to be lower for units sold early in the auction, Allen and Swisher (2000) find that prices tend to increase as the auction proceeds.

Of course, analyzing auctions requires data, and the paucity of such data largely explains why there is not much empirical work studying real estate auction markets. Singapore's Sale of Sites program presents another opportunity to study price properties in an actual auction market. While there are relatively few empirical studies of real estate auctions in general, first-price sealed-bid auctions like Singapore's have been virtually ignored. Thus, one contribution of this paper is that it presents empirical evidence regarding a type of auction largely overlooked in the real estate literature. A second contribution arises from the type of property being auctioned. While several of the existing studies of real estate auctions pertain to property offered for sale as the result of foreclosure or financial duress liquidations, our sample comprises land being offered under normal market conditions. Finally, each auction in our data set comprises a single fully assembled land parcel offered for sale by the Singapore Government. This auction structure avoids introducing the pricing anomalies related to the sales sequence and heterogeneity of property offerings found in earlier studies.

The discussion is organized as follows. Section 2 presents a simple sealed-bid model corresponding to the Singapore land auction and uses the model to show how different factors affect bidding strategies and the resultant land price. Section 3 offers a brief description of the Singapore Sale of Sites auction program. The empirical analysis is reported in Section 4 and the last section concludes.

2 Bidding for Land in an Auction

This is a model of a first-price sealed-bid auction. There is a single seller offering one parcel of land for sale. A finite number of interested buyers determine their bids and then simultaneously present them to the seller. The seller awards the land to the highest bidder at that bid price.

Potential bidders for the specific parcel of land are identified by the expected value they attach to the land, the net return in its developed use, v. Different types of bidders have different anticipated v values. Unless otherwise stated, however, all potential bidders are identical except for their land valuation v. The distribution of bidder types is given by $G(v)$ continuously defined over the range of property values $[v_l, v_u]$. The realized net return to the winning bidder is uncertain ex ante, and equals $v + \varepsilon$, where the stochastic term ε is distributed with mean zero and finite variance, $VAR(\varepsilon)$.

This is a private information game environment.[1] While a given bidder i knows his own type (v) and the number of other bidders who will make offers for the property, bidder i does not know the other types against which he will be bidding in the auction, that is, each bidder does not know the underlying v value other bidders have for the property. Each bidder does know, however, that the population of potential bidders, from which the N actual bidders are drawn, is distributed $G(v)$.

Consider bidder i, whose expected value of the land is v_i. The individual bidder's problem is to offer the bid b_i that maximizes the expected utility from the land. Define P as the probability of bidder i winning the auction. The probability of the single bidder making a high enough bid to obtain the land, given the potential bids from others, is increasing in the own bid, $P' > 0$. Given the stochastic return to other investments or development projects of the bidder is ω, the expected utility is $Eu(\omega + v_i - b_i + \varepsilon)$ when i offers the highest bid and wins the auction and $Eu(\omega)$

[1] McAffee and McMillan (1987) provide an overview of the early auction literature in economics and Quan (1994) and Mayer (1995) discuss real estate applications. Jehle and Reny (2001, 373-399) examine the properties of various canonical auctions using the Nash equilibrium solution concept employed here. Our formulation differs from their cannonical models in several respects: asset value is uncertain ex ante, risk aversion is allowed, and our focus is solely on optimal strategies of bidders in a sealed-bid auction for a single asset.

when he does not. For bidder i the expected utility from the auction is

$$EV = P(b_i)Eu(\omega + v_i - b_i + \varepsilon) + (1 - P(b_i))Eu(\omega)$$

where the expectation operator is understood to be taken with respect to ω and ε.

Since the bids of all N bidders are simultaneously offered as sealed single bids, we consider the auction outcome as a Nash equilibrium. Using the Nash solution concept, the optimal bidding pattern of each individual is determined conditional upon the (optimal) bids of all other participants. Of course, the actual bids of other participants is unknown for a given bidder i when deciding on the bidding strategy. Under our private information assumption, each bidder views the other $N-1$ bidders as random draws from the known distribution of bidder types, $G(v)$.

The optimal bid b_i is that which maximizes the expected utility of bidder i. As such, the optimal bid satisfies the marginal bid condition

$$EV_b = P'(b_i)[Eu(\omega + v_i - b_i + \varepsilon) - Eu(\omega)] - P(b_i)Eu'(\omega + v_i - b_i + \varepsilon) = 0 \quad (1)$$

We assume that the appropriate second order condition (SOC) holds so that

$$EV_{bb} = P''(b_i)[Eu(\omega + v_i - b_i + \varepsilon) - Eu(\omega)] + P(b_i)Eu''(\omega + v_i - b_i + \varepsilon) < 0 \quad (2)$$

The optimality condition (1) implies $Eu(\omega + v_i - b_i + \varepsilon) > Eu(\omega)$, which in turn requires that bid, b_i, be less than the risk-adjusted net asset value. Notice that the optimal bid is monotonic in v_i; implicitly differentiating (1) yields

$$\frac{\partial b_i}{\partial v_i} = -\frac{P'Eu'(\omega + v_i - b_i + \varepsilon) - PEu''(\omega + v_i - b_i + \varepsilon)}{EV_{bb}} > 0$$

under risk neutrality or risk aversion. The bid strategy function $b(v)$ implicitly defined by (1) is the upward-sloped curve aa depicted in Figure 1. This curve shows the optimal bid to be offered by a bidder with underlying land valuation v. When all bidders are identical except for their land valuation, the Nash equilibrium describing the auction outcome is symmetric in the sense that each buyer's bid is solely determined by his land valuation, and is read off of the strategy function $b(v)$ depicted by aa in Figure 1. The highest realized v drawn from $G(v)$ obtains the land with the highest bid. Thus, the comparative static properties of the auction can be inferred using the bid strategy function(s) for the population of potential buyers.

We use the change-of-variables formulation to put marginal-cumulative density ratio in terms of distribution of underlying asset values, a more convenient expression. The optimal bid of bidder type v is $b(v)$ so that the probability that bidder i whose bid is b_i wins the auction is

$$P(b_i) = \left(\int_{b(v_l)}^{b_i} dF(b) \right)^{N-1}$$

where $F(b(v)) \equiv G(v)$ holds using the change-of-variables property of the probability distribution for monotonic $b(v)$. In Nash equilibrium, this implies

$$\begin{aligned} P(b_i) &= \left(\int_{b(v_l)}^{b_i} dF(b) \right)^{N-1} \\ &= \left(\int_{v_l}^{v_i} dG(v) \right)^{N-1} \end{aligned}$$

This means that the marginal-cumulative density ratio can be expressed as

$$\frac{P'}{P} = \frac{g(v_i)(N-1)\left(\int_{v_l}^{v_i} dG(v)\right)^{N-2}}{\left(\int_{v_l}^{v_i} dG(v)\right)^{N-1}} = (N-1)\frac{g(v_i)}{\int^{v_i} dG(v)}$$

so that the optimal bid condition for bidder i can be rewritten as

$$(N-1)\frac{g(v_i)}{\int^{v_i} dG(v)}[Eu(\omega + v_i - b_i + \varepsilon) - Eu(\omega)] - Eu'(\omega + v_i - b_i + \varepsilon) = 0 \qquad (3)$$

The SOC assumed for the maximum also requires

$$D = -(N-1)\frac{g(v_i)}{\int^{v_i} dG(v)}[Eu'(\omega + v_i - b_i + \varepsilon) - Eu'(\omega)] + Eu''(\omega + v_i - b_i + \varepsilon) < 0.$$

The first question concerns what happens as the number of participating bidders rises. Implicit differentiation of the optimal bid condition (3) leaves

$$\frac{\partial b_i}{\partial N} = \frac{g(v_i)[Eu(\omega + v_i - b_i + \varepsilon) - Eu(\omega)]}{-D\int_0^{v_i} dG(v)} > 0$$

where the sign follows from $D < 0$ and (3). This result is what is usually argued on intuitive grounds: *the optimal bid from each type of bidder rises as the number of bidders in the auction rises,* shifting the bid strategy curve from aa to cc in Figure 1. In addition, (3) reveals that b_i approaches the risk-adjusted expected value of the property to the bidder with greater N so that the optimal bidding strategy approaches the neoclassical competitive market bid price characterization in the limit.[2] Further, since all individual bid prices rise with N while at the same time the probability of drawing a higher-value bidder as the number of bidders rises as N rises, *the above result implies a higher expected selling price in the auction with greater number of bidders.*

Mayer (1995) leads to a similar conclusion but for a different reason. He argues that auctions lead to sales prices that are lower than generally obtained from direct negotiation because auctions limit the market exposure of the asset being sold. Put simply, auctions yield lower prices than direct sales because the limited time frame of the auction reduces the sample of available buyers and lowers the likelihood of a higher value buyer (higher v_i in our model) in the market during the limited selling period. Thus, increasing the number of bidders increases the likelihood of a high value bidder in the pool of buyers, thereby increasing the expected auction price.

In contrast, in our model increasing the sample of potential buyers increases expected sales price both because of the greater likelihood of higher value buyers in attendance as well as changes in each buyer's optimal bidding strategy. Each buyer's optimal strategy balances the probability of winning the auction against the lower net return from a higher bid, and the optimal bid is generally lower than that which yields zero risk-adjusted profit. Increasing the number of bidders increases the optimal bid of each potential buyer because increasing the number of rival bidders lowers each bidder's marginal probability of winning, providing an incentive for each bidder to work harder to obtain the asset by increasing his bid. Added to the greater likelihood of drawing in a high value bidder (as in Mayer (1995)), both effects together lead to

[2] The opportunity cost of a land developer is $Eu(\omega)$ in our model. The expected utility from the land for developer type v is $Eu(\omega + v - b + \varepsilon)$. The developer's bid price for the land is that which equates the expected utility from the land and his opportunity cost, or $Eu(\omega + v - b + \varepsilon) = Eu(\omega)$, which is the condition derived from (3) in the limit as $N \to \infty$.

higher expected selling price in the auction as the number of bidders rises.

Given the expected auction price approaches the competitive bid price in the limit as the number of bidders rises, it should not be surprising that many of the auction solution characteristics qualitatively resemble those of the neoclassical bid price equilibrium. As an example, consider how different innate valuations of the land changes the bid structure, hence the auction price. Modeling a greater innate land value to bidders as a rightward shift in the distribution $G(v)$, define the expected property values $\theta_v + v$, where θ_v is a nonstochastic shift parameter. Substituting for v in the optimal bid condition (3) and differentiating yields the comparative static result, evaluated at $\theta_v = 0$:

$$\left(\frac{\partial b_i}{\partial \theta_v}\right)_{\theta_v=0} = -\left(\begin{array}{c} (N-1)\frac{g(v_i)}{\int_0^{v_i} dG(v)} Eu'(\omega + v_i - b_i + \varepsilon) \\ -Eu''(\omega + v_i - b_i + \varepsilon) \end{array}\right) D^{-1} > 0$$

where sign follows using non-risk loving assumption, $u'' \leq 0$, and the fact that the marginal-cumulative density ratio $g/\int dG$ is unchanged with the distribution translation used here. *Thus, the rightward shift in the property value distribution (or equivalently, the distribution of bidder types) increases the optimal bid of each type of bidder, thereby implying a higher expected selling price in the auction.* This is certainly intuitively plausible; the greater the underlying value of the property from the perspective of all potential bidders, the higher the equilibrium auction price. In terms of the empirical analysis, this result ties the standard underlying valued characteristics of the land, like location-specific amenities, neighborhood affects, or accessibility to desired locations, to the expected auction price.

We can similarly show that *larger multiple-project bidders will bid more for the land.* To do so, denote $E[\omega] = \overline{\omega}$ so that an increase in $\overline{\omega}$ pertains to a larger multiple-project bidder. Using $D < 0$ and (3) we have

$$\frac{\partial b_i}{\partial \overline{\omega}} = -\left((N-1)\frac{g(v_i)Eu'(\omega)}{\int^{v_i} dG(v)} - D\right) D^{-1} > 0$$

On the other hand, if larger operations running multiple projects enjoy portfolio effects that lower the variance of outcomes, this lower variance of other project net returns has its own risk effects on the optimal bid for this parcel of land. Let θ_ω denote the distribution risk parameter such that $dVAR(\omega)/d\theta > 0$. Use $\omega = \overline{\omega} + \theta_\omega \varepsilon_\omega$ and differentiate the optimal bid condition with respect to θ_ω, evaluated the result at $\theta_\omega = 1$ to find the effect of an increase in the mean-preserving-spread of ω as

$$\frac{\partial b_i}{\partial \theta_\omega} = \left(\begin{array}{c} -(N-1)\frac{g(v_i)}{\int^{v_i} dG(v)} E[u'(\omega + v_i - b_i + \varepsilon)\varepsilon_w - u'(\omega)\varepsilon_\omega] \\ +E[u''(\omega + v_i - b_i + \varepsilon)\varepsilon_\omega] \end{array} \right) D^{-1} \quad (4)$$

$E[u'(\omega+v_i-b_i+\varepsilon)\varepsilon_w - u'(\omega)\varepsilon_\omega]$ takes the sign of $COV[E_\varepsilon[u'(\omega+v_i-b_i+\varepsilon)-u'(\omega)], \varepsilon_\omega]$. Using the properties of similar-dissimilar ordering to evaluate this covariance,

$$\begin{aligned} \frac{\partial E_\varepsilon[u'(\omega + v_i - b_i + \varepsilon) - u'(\omega)]}{\partial \varepsilon_\omega} &= E_\varepsilon u''(\omega + v_i - b_i + \varepsilon) - u''(\omega) \\ &\approx E_\varepsilon u''(\omega) + E_\varepsilon u'''(\omega)(v_i - b_i + \varepsilon) - u''(\omega) \\ &= E_\varepsilon u'''(\omega)(v_i - b_i + \varepsilon) \\ &= u'''(\omega) E_\varepsilon[v_i - b_i + \varepsilon] \\ &= u'''(\omega)(v_i - b_i) > 0 \end{aligned}$$

where E_ε denotes the expectation taken over ε. The second line takes the second order approximation to the first *r.h.s.* term, the third and fourth lines exploit the fact that ω can be moved outside the E_ε operator, and the fifth line uses $E[\varepsilon] = 0$ and $u''' > 0$ under constant or decreasing absolute risk aversion (CARA or DARA). Thus (4) implies non-increasing absolute risk aversion is sufficient to establish

$$\frac{\partial b_i}{\partial \theta_\omega} < 0$$

so that *bidders who enjoy lower total portfolio risk from greater diversification in other projects or investments have the incentive to bid more for the parcel of land being auctioned*. Graphically, the bid strategy curve for diversified bidders lies above that pictured for less diversified bidders, e.g., *cc* relative to *aa* in Figure 1.[3]

Finally, the usual characterization of CARA or DARA is sufficient to establish that *greater riskiness of development returns leads to lower bids and expected auction price.* This result is easily shown. Define the risk parameter θ_ε such that land

[3] Note that the fact that one bid strategy curve lies above another does *not* imply that buyers with the lower bid strategy curve cannot win the auction. It just implies that for lower bid strategy buyers to win the auction, the "draw" of higher bid strategy curve buyers will have to end up being from the lower end of the value distribution.

value are $v + \theta_\varepsilon \varepsilon$. An increase in θ_ε increases the spread of the realized land value ($dVAR(v + \theta_\varepsilon \varepsilon)/d\theta_\varepsilon > 0$) without affecting the mean ($dE[v + \theta_\varepsilon \varepsilon]/d\theta_\varepsilon = 0$) and so represents a mean-preserving increase in $\varepsilon-$risk. Substituting into the optimal bid condition (3), implicitly differentiating, and evaluating the result at $\theta_\varepsilon = 1$ yields

$$\frac{\partial b_i}{\partial \theta_\varepsilon} = \left(E[u''(\omega + v_i - b_i + \varepsilon)\varepsilon] - (N-1)\frac{g(v_i)}{\int^{v_i} dG(v)} E[u'(\omega + v_i - b_i + \varepsilon)\varepsilon] \right) D^{-1} < 0$$

using $E[u'(\omega+v_i-b_i+\varepsilon)\varepsilon] < 0$ under risk aversion and $E[u''(\omega+v_i-b_i+\varepsilon)\varepsilon] > 0$ under CARA or DARA. Greater development returns riskiness shifts the bid strategy curve downwards from cc to aa in Figure 1, leading to lower bids hence a lower expected auction price.

3 Sale of Sites (SOS) Auction Program in Singapore

The Singapore property market suffered a variety of afflictions in the early 1960s: overcrowding, dilapidated housing, large numbers of squatters, poor hygiene and sanitation, limited social amenities and congested traffic. Recognizing the importance of involving the private sector to transform the urban landscape of the new nation, the Singapore Government initiated the Sales of Sites (SOS) program. Under this program, the government used its compulsory powers to acquire fragmented urban land plots, amalgamating them and then offering them free of encumbrances to the private sector for development.

All of the site sales are handled by two local government agencies, the Urban Redevelopment Authority (URA) and the Housing and Development Board (HDB), with the URA handling 58% of development sites and the HDB handling 42%. The HDB is primarily responsible for sales of sites located within the boundary of public housing estates, which are usually designated for lower end private housing or sub-urban style commercial development. The URA, on the other hand, handles the sale of sites that are located outside the public housing estates. For residential developments, the URA sites are usually located within established private residential areas, while the commercial sites are mostly located within the commercial business district

(CBD).

The land is sold through a first-price sealed-bid auction. The process is, briefly, as follows. When a development site is released for sale, interested bidders are invited to purchase a Developer's Packet containing the planning and design guidelines for the site and other specific conditions for the sale. The sites usually entail a leasehold tenure of 99-years for commercial, hotel and private residential development and 60-years for industrial development. Depending on the complexity of the proposed development and other constraints on the site, interested bidders are given between two and four months to carry out their due diligence and prepare the tender submission. By noon on the closing date of the auction, the bidders must deposit their sealed-bid together with a deposit equivalent to 10% of the bid amount. The bids are opened and the names of all bidders and their respective bids are posted on the same day. The site is then awarded to the highest bid exceeding the reserve price.[4] Thus, in a sealed-bid auction in Singapore, a given bidder may not know with certainty the number of other bidders who will make offers for the property until the tender results are revealed. Whilst the number of actual potential bidders in the market is small, especially for large development sites, some auctions may attract new bidders. Hence, sealed-bid is the preferred method of sale in Singapore (instead of an open auction) because it is believed to reduce the probability of collusion among potential bidders.

Once the highest bidder has been awarded the site, the government agency monitors the development progress closely in order to ensure that the outcome is in accordance with the planning and technical requirements stipulated in the auction submission. The successful bidder is also prohibited from selling the site (that is, the leasehold) to outside parties. In addition, the bidder must complete the development within the specified time frame in order to avoid punitive fines for late completion.

In total, 202 public sites were sold for residential development between 1990 and

[4] While past auctions considered planning concepts, design merits and other tender conditions, the current auction system bases awards on price alone. The reserve price, which is not revealed to bidders, is set equal to 85% of the Chief Valuer's assessed market value for the development site. The valuation, which is submitted by the Chief Valuer in a sealed envelop before the tender closing date, is opened at the same time as the received bids.

2002. Table 1 reports the breakdown of sales by year. No sales took place between 1998 and 1999 while the SOS program was suspended during the extended property market slump in Singapore. Of the 202 sites in our sample over 1990-2002, 191 were for purely residential developments. The remaining 11 sites allowed mixed-use developments with a substantial residential component; 9 included some retail activities and 2 coupled the residential component with development for office use.

The majority of sites (140) was for high-rise multiple-unit residential developments– either as apartments (with minimal communal facilities), condominiums (larger developments with a full range of communal facilities), or executive condominiums (with a 10-year restriction on resale and occupation). Sixty two of the sites were designated for low-rise landed developments (that is, bungalows, detached, semi-detached, and linked houses).

Most successful bidders are single buyers (170 sites); 32 sites were acquired by joint-venture developers. One half of the successful purchasers are publicly listed firms and one half are privately owned (each type acquired 101 sites). Only 13 development sites were acquired by companies linked to the government. In addition, almost all sites were obtained by locally incorporated companies. Also, not surprisingly, most winning bidders are either real estate firms or firms with prior real estate development experience.

Table 2 defines the variables used in the empirical model described below and Table 3 reports the descriptive statistics for the entire sample of 202 sold sites. Referring to the latter, the winning bid price ranges from a minimum of S$2.7 million to S$682.8 million. The average winning bid price for the 202 parcels is S$89.7 million. The average parcel size is 19,115 sq. m. and the average plot ratio (the allowed ratio of floor space to land area) is 1.96.

Singapore occupies a small physical area. The greatest distance of a sold plot to a subway station is only slightly above 4 km. Similarly, the development site farthest from the CBD is only 23 km. In view of the short distances involved, we expect a relatively flat rent gradient in Singapore.

One average, each auction attracted 6.3 bids. The most popular site attracted 20 bids and the 11 least popular sites attracted only one bid each. (Recall, though, that even single bidders must bid against the uncertain reservation price so that single bidder auctions resemble 2 bidder auctions in our model.)

4 The Empirical Price Model

The hedonic price function implied by the auction framework in Section 2 identifies the relevant variables as those reflecting underlying value (as reflected in the v distribution function), buyer characteristics (as reflected in the $\omega-$risk and $\varepsilon-$risk terms), and the degree of competition (as reflected by the number of competing bidders and number of alternative sites offered for sale within the same time frame). We use the popular semi-log functional form, regressing the logarithm of selling price on the variables identified below. Table 4 reports the relevant parameter estimates for six versions of the empirical model.

Overall, the estimated models are significant and explain over 80% of the observed land price variation. This is surprisingly high in light of earlier empirical research on vacant land markets (Colwell and Munneke, 1997).

4.1 Site attributes

The first group of variables are included in the price functions to pick up the effects of site location, parcel size, and other site-specific characteristics. The primary parcel location attributes are captured by the distance from the commercial business district (*CBD*) and the distance from the nearest metro station (variously measured by *METRO DIST*, *CLOSE*, and *WALK*). The *CBD* coefficient is negative and significant in almost all of the models. This is a straightforward result and is as expected.

On the other hand, the value of proximity to a metro station is a little more complicated. The positive coefficient for the *METRO DIST* variable in model 1 is surprising at first. But there are two competing location effects of metro station proximity: easy access to mass transportation and the countervailing negative externality from pedestrian congestion, noise, or other negative externalities from the metro station. Our metro distance variable appears to be picking up a combination of both effects. In order to try sorting out these competing effects on land value, we define

CLOSE as a binary variable indicating land parcels lying within 0.3 km of a metro station and *WALK* as a variable indicating land parcels within easy walking distance of a metro station, which is assumed to be 0.5 km. If the negative externalities from the metro station are localized, as we expect they are, then *CLOSE* should pick up the differential effect of the externality on the immediate neighborhood while *WALK* picks up the positive value of accessibility. The estimates from models 2-6 in Table 4 are consistent with the expected pattern. The *CLOSE* coefficient is negative and significant in all cases, picking up the extremely localized negative externality of the metro station. The *WALK* coefficient is positive but insignificant in all of the models.[5] This pattern either indicates that metro station access is sufficiently ubiquitous in the sample areas to not lead to differential effects on price or that surface transportation provides a good substitute for the metro system in the residential areas in our sample. The latter is consistent with the widely-held notion that the integrated network of subways and buses provides an efficient public transportation network for the city. Further, road congestion is not severe for taxis and private automobiles. In conjunction with the small area occupied by the city, the mild road congestion means that surface travel is relatively easy; travel time from the remote area to the CBD is generally only 30 minutes.

LnSIZE is the log of lot size and is included in the hedonic price function to control for the nonlinear relationship between size and price attributed to land assembly and subdivision costs (Colwell and Munneke, 1997, 1999; Colwell and Sirmans, 1980; Thorsnes and McMillen, 1998). The significantly positive coefficient found in all of the estimated models is evidence of plottage. Our results suggest that the government has solved the land assembly problem for developers by using its police power to consolidate individual vacant plots into the single contiguous parcels offered for sale in the auction.

PLOT RATIO reflects the maximum allowed floor area-land area ratio for the site. Like lot size zoning in the U.S., this restriction can be envisioned as following the market or as a binding regulatory constraint, the former case yielding insignif-

[5] The variable remains insignificance when walking distance is extended to include sites as far away as 0.8 km from a metro station.

icant and the latter significant price effects. In our application, the coefficient is significantly positive; allowing greater structural density increases land value. Thus, this constraint is binding on developers in our sample, which is consistent with the common view held by market participants.

We also include the variable *MIXED USE* in model 4 to capture site value effects from allowing mixed retail or office space in the primarily residential development. (The retail or office uses are typically restricted to the ground floor of multi-story developments.) The estimated coefficient is positive but not significant. The residence-only restriction on most of the sold sites is not binding on the market, that is, the use restriction appears to follow the market in Singapore.

4.2 Buyer characteristics

Our next question concerns why buyer characteristics might systematically affect selling prices. Price discrimination is one classic explanation for systematic price differences across types of buyers. While this argument is not broadly applicable, it remains relevant in special cases. In his study of land pricing in a large Ghanian city, Asabere (1981) pointed out that the traditional institutions give local Ashanti chiefs power to dominate the local land market. The chiefs practice price discrimination in the allocation of land by favoring Ashanti over non-Ashanti land users; the former only pay 55% of the land price that would prevail in the absence of the chiefs' local monopoly power. The price discrimination persists in equilibrium because the local chiefs are able to prevent the Ashantis from engaging in arbitrage with non-Ashantis because all land transfers are subject to their approval. But most real estate markets operate under private property regimes that are closer to fee simple. In such cases, price discrimination cannot persist.

The literature offers other rationales for why buyer characteristics might affect the selling price of real estate assets. For example, Sirmans, Turnbull, and Benjamin (1990) and Sirmans and Turnbull (1993) use search theory to examine how buyer and seller characteristics can affect selling prices of houses, focusing on how different characteristics or information sets alter the optimal search strategy of buyers and reservation prices of sellers. In a different vein, Harding, Knight, and Sirmans (2003), and Harding, Rosenthal, and Sirmans (2003) consider how the bargaining skill or bargaining power of buyers relative to sellers is reflected in selling prices of houses. Buyer characteristics are then reflected in selling prices to the extent that the characteristics systematically vary with relative bargaining skill or power.

In the auction model explained here, however, buyer characteristics affect the optimal bidding strategy. This effect is the auction analogue to the neoclassical bid-rent model in which different types of buyers (or, more accurately, different categories of land uses) have bid rents that lie either above or below that of their rival buyer types. In this vein, Chicoine (1981) argues that the type of buyer and seller involved in the sale (whether an individual, corporation, partnership or land trust) should be expected to affect the selling price of fringe farmland. Chicoine's rationale can be demonstrated within the context of the neoclassical bid-rent model; differences in market information, access to capital, legal status, as well as non-pecuniary preferences all affect the profitability of the parcel of land to that particular type of buyer, hence the bid rent and selling price. Nonetheless, Chicoine's rationale also fits within the auction framework described earlier.

Following earlier studies, we use observable buyer characteristics as proxies for likely differences in information, ability, or incentives.[6] The first of the buyer characteristics variables in our models, *EXPERIENCE*, is a binary variable indicating whether or not the highest bidder has previous experience as a developer. Our supposition is that experienced developers will have greater ability to extract higher expected returns from a given proposed project. At the same time, the more experienced developer will have better information or greater ability to foresee and react to contingencies, leading to lower project riskiness. In terms of the auction model, the higher expected returns means that more experienced developers populate the upper range of expected project value distribution while the lower $\varepsilon-$risk leads to an upward shift in the bid strategy curve in Figure 1; both effects lead to higher bids, hence higher selling prices when experienced developers are the highest bidders.[7]

[6] Chicoine (1981), Sirmans, Turnbull, and Benjamin (1990), Sirmans and Turnbull (1993), Harding, Knight, and Sirmans (2003), and Harding, Rosenthal, and Sirmans (2003).

[7] A contrary argument can be offered as well. If inexperienced firms systematically over-estimate the expected returns from the land parcel, then this aspect of inexperience leads such firms pay more

The second variable reflecting observable buyer characteristics is *PUBLIC*, a binary variable indicating whether the highest bidder is publicly listed or privately owned. Publicly listed companies have access to lower cost capital than do privately owned firms, capital they can exploit to further reduce their profit risk with portfolios of diverse development projects. In terms of our auction framework, publicly listed companies have lower $\varepsilon_{\omega}-$risk, which also shifts the bid strategy curve upwards in Figure 1 from *aa* to *cc*. This leads to higher selling prices when publicly listed firms are the highest bidders.

Finally, we include the binary variable *JOINT* indicating whether or not the successful bid was made by a joint venture. Given the portfolio effect of the joint venture is to reduce $\varepsilon_{\omega}-$risk much like the publicly traded relative to the privately owned firm, we expect joint ventures to have higher optimal bids, ceteris paribus, leading to a higher selling price.

The estimated coefficients on these variables in the hedonic price function are robust across all of the models. Looking at the estimates reported in Table 4, publicly listed companies do pay more for the land than do their privately owned counterparts, a result consistent with the auction and bid-price models. On the other hand, we find that neither prior development experience nor joint venture structure have significant price effects.

4.3 Competition and information

One point emphasized earlier was that the auction model leads to precisely the same predictions as the neoclassical bid-price model with respect to all of the examined underlying parameters–except for one: the degree of competition. The neoclassical bid-price model assumes a large number of atomistic potential buyers in order to drive the bid of each type to where risk-adjusted profit is zero. The auction model, however, presents an explicit framework tying the number of rival buyers to each buyer's optimal bidding strategy, thereby tracing the competition-price nexus that

for the land than their more experienced counterparts, ceteris paribus. Of course, the risk effect identified in the text still reduces the optimal bid of inexperienced firms (unless they systematically under-estimate the project risk as well), leading to a net ambiguous effect.

cannot be formally addressed within the neoclassical bid-price model.

Our basic measure of competition is simply the number of bidders in the auction. In the auction model, increasing N, ceteris paribus, shifts the optimal bid strategy function in Figure 1 upwards from aa to cc. As this holds for all participants, increasing N increases the expected selling price as well. The variable *NUMBER* is the number of bidders in the empirical models 1-5 in Table 4. The theoretical auction model predicts a positive effect on selling price and, indeed, in all of the estimated models the number of bidders has a significant positive effect on selling price. Simply put, the larger the number of competing buyers, the closer the equilibrium comes to the neoclassical bid-price equilibrium.

In models 3-6 we introduce a variety of other measures of competition. Since none of these alternatives are as closely related to the competition measure in the theoretical model as is *NUMBER*, they are to some extent ad hoc proxies. Nonetheless, they yield additional insights and, if nothing else, reaffirm the robustness of the above result across a variety of specifications. Section 2 claimed that an auction with a single bidder can be viewed as a two-bidder auction, given that the single bidder in Singapore's SOS auctions must bid against the (uncertain to bidder) reservation price. Still, it is reasonable to wonder if such single-bidder auctions really do conform with theory. In order to test whether or not single bidder auctions affect prices differently than do multiple bidder auctions, we introduce the binary variable *SINGLE* to pick up systematic effects associated with this characteristic in models 3-6. As predicted by the theory, the single bid does not lead to a different pricing outcome once the effects of minimal competition are taken into account; in models 3-5 the *NUMBER* variable is highly significant and positive while the *SINGLE BID* dummy variable is insignificant in every case. Only when the *NUMBER* variable is removed from model 6 does the *SINGLE* variable become significantly negative. This case, of course, is simply picking up the effect of greater competition as measured by the now-omitted number of bidders variable. Single bidder auctions yield lower selling prices than others solely because the level of competition among buyers is minimized in such auctions. The estimates reveal no evidence that the simple auction model breaks down for the single bidder case.

We also introduce *PRICE DIST* in models 1-6. This variable is intended to pick up the effects of readily available price information for surrounding parcels on the selling price of a particular parcel. It is calculated as the average price (S$ psm) of the five most recent land sales weighted by their distance (in km) to the subject site. To measure the information conveyed by earlier sales, *PRICE DIST* is constructed using only sales that took place before the subject auction date. Although intended to capture information about the surrounding market, the spatial weighting in this variable may also be picking up any price arising from unmeasured amenities or other neighborhood-specific effects. In either case, the auction model predicts a positive relationship between this variable and selling price. If the variable simply conveys information about conditions in the surrounding market, whether supply and demand conditions or underlying neighborhood amenity values, then higher values of *PRICE DIST* indicate greater underlying value for the parcel being auctioned (that is, a higher v, reflected in a rightward movement along the optimal bid strategy curve in Figure 1). Consistent with our expectations, the estimated coefficients on this variable are positive and highly significant in all of the estimated models. Can and Megbolugbe (1997) find similar spatial relationships among selling prices of houses in a non-auction setting.

Finally, models 5 and 6 include additional proxies that intended to measure competition. *COMP* is calculated as the total number of forthcoming bids divided by the total number of other auctions taking place within 30 days before and after the auction for the site. This variable is intended to pick up the effects of competing auctions; we expect that a greater number of auctions (which reduces *COMP*) reduces the competition among bidders for any given site, thereby reducing bids and selling price. Similarly, we expect that a greater number of potential buyers participating in other auctions (which increases *COMP*) reflects a greater level of overall competition in the land market, leading to higher bids and selling price. If our expectations are correct, then these two effects lead to a positive coefficient on *COMP* in the land price function. The estimate only is significantly positive in model 6 when the number of bidders is omitted from the regression.

We also include the number of other auctions taking place within the same 60-day window around a given auction, *OTHER AUCT*. If the auctions were being offered by competing sellers, then our argument in the previous paragraph would lead us to expect a negative *OTHER AUCT* effect on selling price. In the SOS program, however, there is a monopoly seller: the government. Thus, the estimated effect of *OTHER AUCT* on price instead will reveal the extent to which the two government agencies are successfully exploiting their monopoly power by timing site auctions to yield greater total returns. Models 5 and 6 both reveal a significant positive effect of *OTHER AUCT* on selling price. Apparently, the government has been successfully spacing the site sales to take advantage of market conditions, offering more sites for sale in stronger markets and cutting back in weaker markets. The temporary cessation of auctions during the downturn of 1998-99 reported in Table 1 is consistent with this interpretation.

5 Conclusion

This paper examines the price formation process under small numbers competition, reporting empirical evidence from first-price sealed bid land auctions undertaken over an extended period in Singapore. Auction theory predicts that bid prices are less than the zero-profit asset value in these first-price sealed-bid auctions and that the optimal bids from potential buyers rise with the number of bidders. When coupled with Mayer's (1995) argument that increasing the number of bidders increases the likelihood of a high-value bidder participant, both effects together provide the prediction that the expected auction price rises with the number of active bidders, a robust empirical result observed in the Singapore auction data.

The empirical estimates also provide evidence of plottage and show that government land use controls on allowed structural density are binding constraints on developers. On the other hand, restrictions on mixed land uses are generally not binding and follow the market. Auction prices rise with greater auction frequency over the time period examined, which suggests the government agencies are successful in their attempts to manage the number and frequency of auctions to take advantage of periods of market strength and avoid further depressing property values during periods of market decline.

Previous studies use information or search cost differences across agents (Sirmans, Turnbull, and Benjamin, 1990; Sirmans and Turnbull, 1993) or differences in bargaining power (Harding, Knight, and Sirmans, 2003; Harding, Rosenthal, and Sirmans, 2003) to explain how buyer or seller characteristics can affect real estate asset prices. The auction model shows how differences in information or development skills are directly reflected in bidding strategies, providing a simple channel through which buyer characteristics affect the sales price. We find that neither prior development experience nor joint venture structure significantly affect bid price, results that are both surprising and at variance with the auction model prediction. Finally, the empirical estimates show that publicly listed companies bid more than do privately held companies. This result by itself implies that winning an auction will increase the capitalized value of closely held companies more than the effect found by Ching and Fu (2003) and Ooi and Sirmans (2004) for publicly traded companies.

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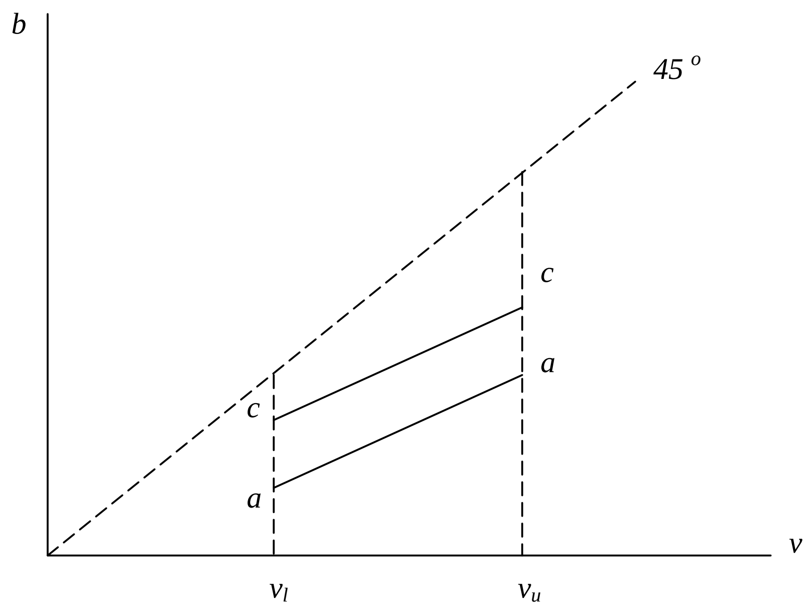

Figure 1. Bid strategy function *b(v)*

Table 1: Breakdown of sites sold by year

Year	*No.*	*Average Price (S$ million)*	*Total Price (S$ million)*
1990	5	25.414	127.070
1991	6	39.497	236.982
1992	13	34.398	447.174
1993	16	75.020	1,200.320
1994	24	106.626	2,559.024
1995	29	74.229	2,152.641
1996	33	97.970	3,233.010
1997	38	128.069	4,866.622
2000	21	83.775	1,759.275
2001	12	90.750	1,089.000
2002	5	88.718	443.590
Total	**202**	**89.677**	**18,114.708**

* US1 equals approximately S$ 1.80 as at end 2002.

Table 2. Variable Definitions

- PRICE is the winning bid in S$.
- SIZE is the area of the land parcel in sq m.
- CBD is the distance in km to the Central Business District.
- METRO DIST is the distance in km to the nearest metro station.
- CLOSE is a binary variable indicating land parcels lying within 300 m of a metro station.
- WALK is a binary variable indicating land parcels lying within easy walking distance from the metro station, which is assumed to be 0.5 km.
- PLOT RATIO reflects the maximum allowed floor area-land area ratio for the site.
- MIXED USE is a binary variable indicating land parcels which allow ancillary retail and office space in primarily residential development.
- EXPERIENCE is a binary variable indicating or not the highest bidder has previous experience as a developer.
- PUBLIC is a binary variable indicating the highest bidder is a publicly listed company.
- JOINT is a binary variable indicating the successful bid is by a joint venture.
- NUMBER is the number of bidders in the auction.
- SINGLE indicates only one bid submitted for a particular site (11 such incidents).
- PRICE DIST is the average price (S$ psm) of five comparable land sales prior to bid weighted by their relative distance to the subject site.
- COMP is the total number of bids divided by total number of auctions for other land sales within a fixed window of 30 days before and after the observed land sale. This is intended to measure the relative strength of vacant land demand around the time of the observed sale.
- OTHER AUCT is the total number of auctions within a fixed window of 30 days before and after the observed land sale.
- TIME INDEX is a running number from 1 to 13 to capture the time effects through the study period. 1990 =1, 1991 =2, …., 2002=13.

Table 3. Descriptive Statistics

Descriptive statistic is based on 202 observations.

Variable	Mean	Std.Dev.	Minimum	Maximum	Skewness	Kurtosis
PRICE	89,676,500	82,340,200	2,765,310	682,800,000	2.441	15.261
SIZE	19,115	16,354	910	125,913	2.859	16.078
CBD	9.722	4.595	0.924	23.080	0.261	2.732
METRO DIST	1.311	0.953	0.080	4.060	0.890	2.905
CLOSE	0.114	0.318	0.000	1.000	2.425	6.877
WALK	0.297	0.458	0.000	1.000	0.886	1.780
PLOT RATIO	1.959	0.995	0.800	8.400	1.341	9.871
MIXED USE	0.050	0.217	0.000	1.000	4.143	18.162
EXPERIENCE	0.886	0.318	0.000	1.000	-2.425	6.877
PUBLIC	0.495	0.501	0.000	1.000	0.020	0.995
JOINT	0.158	0.366	0.000	1.000	1.866	4.478
NUMBER	6.267	3.462	1.000	20.000	0.975	4.320
SINGLE	0.050	0.217	0.000	1.000	4.143	18.162
PRICE DIST	2,714.1	966.7	425.2	6,625.0	0.383	4.305
COMP	6.128	1.997	0.250	10.667	0.295	3.339
OTHER AUCT	5.926	3.483	1.000	13.000	0.401	2.097
TIME INDEX	6.876	2.872	1.000	13.000	0.265	2.569

Table 3. Hedonic Land Auction Price Function Estimates

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	7.1278** (0.5355)	7.14976** (0.5196)	6.4583** (0.4238)	6.3723** (0.4092)	5.7168** (0.4785)	5.8334** (0.4803)
lnSIZE	0.93106** (0.0510)	0.9043** (0.0451)	0.9961** (0.0385)	1.0036** (0.0369)	1.0330** (0.0383)	1.0244** (0.0378)
CBD	-0.0170* (0.0079)	-0.0002 (0.0025)	-0.0271** (0.0065)	-0.0275** (0.0064)	-0.0296** (0.0062)	-0.0329** (0.0066)
METRO DIST	0.0173* (0.0080)					
CLOSE		-0.2523** (0.1076)	-0.2940** (0.0966)	-0.2860** (0.0993)	-0.3151** (0.1054)	-0.2761** (0.1110)
WALK		0.0158 (0.6451)	0.0565 (0.0660)	0.0588 (0.0664)	0.0693 (0.0604)	0.0680 (0.0628)
PLOT RATIO	0.4224* (0.055)	0.4657** (0.0551)	0.4677** (0.0510)	0.4538** (0.053)	0.4680** (0.0521)	0.4862** (0.0534)
MIXED USE				0.1938 (0.1528)	0.2453 (0.1688)	0.2614 (0.1671)
EXPERIENCE	-0.0093 (0.1051)	0.0159 (0.0979)	-0.05231 (0.0976)	-0.0302 (0.1001)	0.0087 (0.0951)	-0.0033 (0.1029)
PUBLIC	0.1108* (0.0568)	0.1124* (0.0574)	0.1439** (0.0545)	0.1497** (0.0542)	0.1670** (0.0529)	0.1870** (0.0561)
JOINT	-0.0828 (0.0736)	-0.0826 (0.0729)	-0.0791 (0.0684)	-0.0841 (0.0683)	-0.0816 (0.0697)	-0.0654 (0.0679)
NUMBER	0.0430** (0.0108)	0.0498** (0.0111)	0.0434** (0.0099)	0.0445** (0.0098)	0.0402** (0.0112)	
SINGLE			-0.20461 (0.1579)	-0.2058 (0.1652)	-0.0219 (0.1705)	-0.3906** (0.1607)
PRICE DIST	0.0019** (0.00004)	0.0019** (0.00004)	0.0003** (0.00004)	0.0002** (0.00004)	0.0002** (0.00004)	0.0002** (0.00004)
COMP					0.0171 (0.0206)	0.0537** (0.0182)
OTHER AUCT					0.0334** (0.0103)	0.0358** (0.0107)
TIME INDEX	0.0571** (0.0146)	0.0507** (0.0153)	0.0471** (0.0134)	0.0498** (0.0132)	0.0700** (0.0152)	0.0692** (0.0153)
Adj. R^2	.8342	.8332	.8611	.8619	.8693	.8594
F-statistic	102.15**	92.29**	101.23**	94.16**	87.03**	85.70**
d.f.	191	190	182	181	179	180

Notes:
Dependent variable is LnPRICE. Estimated standard errors are in parentheses.
*Significant at 10% level (one tail).
**Significant at 5% level (one tail).